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Departamento de Economía de la Empresa
Universidad Carlos III de Madrid
Calle Madrid, 126
28903 Getafe (Spain)
Fax (34-91) 6249607

EXPENDITURE TRENDS IN US ADVERTISING: LONG-TERM EFFECTS AND STRUCTURAL CHANGES WITH NEW MEDIA INTRODUCTIONS *

Mercedes Esteban-Bravo¹, José M. Vidal-Sanz², and Gökhan Yildirim³

Abstract

Historically US Media channels have competed to attract advertising expenditure from marketing. This has been a fierce battle, where, every few years, incumbents have been shattered by the introduction of a new media such as TV, Yellow Pages, Cable and the Internet. In this paper we will analyze and discuss the dynamic trend in advertising expenditure for ten different advertising media channels in the U.S., by estimating the long-term equilibrium between these time series, and their equilibrium cross-elasticities. We will also analyze how they are related to the business cycle, both at the aggregated level and specifically for each media. To this end, it is crucial to consider simultaneously the impact of new media introductions over the incumbents, estimating the potential effects of structural changes. Both, the introduction effects and the long-term equilibrium relationship between two media can be very different. In particular, we will study the influence of the Internet.

Keywords: Advertising Expenditure, Media, Structural Breaks, Time Series..

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¹ Mercedes Esteban-Bravo, Department of Business Administration, University Carlos III de Madrid, C/ Madrid 126, 28903 Getafe (Madrid), Spain; tel: +34 91 624 8921; fax: +34 91 624 8921; e-mail: mesteban@emp.uc3m.es

² Jose M. Vidal-Sanz, Department of Business Administration, University Carlos III de Madrid, C/ Madrid 126, 28903 Getafe (Madrid), Spain; tel: +34 91 624 8642; fax: +34 91 624 9607; e-mail: jvidal@emp.uc3m.es

³ Gökhan Yildirim, Department of Business Administration, University Carlos III de Madrid, C/ Madrid 126, 28903 Getafe (Madrid), Spain; tel: +34 91 624 8921; fax: +34 91 624 8921; e-mail: gyildiri@gmail.com

Introduction

The history timeline of the US media in the 20th century shows a steady rise in advertising expenditure driven by the increasing corporate activity, but this growth is combined with periods of restructuring by diversification within the available mass media technologies. As new media channels were developed, they competed with incumbents to attract billions of advertising dollars. The fight between the old traditional media such as newspapers, magazines, and radio, and the newer entrants such as the Internet, cable and Yellow Pages, has been particularly significant until now and probably will remain fierce for some decades to come. Reports by key organizations such as the Internet Advertising Bureau (IAB), the Newspaper Association of America (NAA), and research companies such as Kantar Media Intelligence, eMarketer and AC Nielsen are tracked by marketing managers to allocate their advertising budgets to each channel.

Macroeconomic cycles also play a role in the dynamics of this industry. There is a significant amount of literature about the link between advertising and recessions; for an overview see Tellis and Tellis (2009). Corporate reactions to recessions are quite heterogeneous, some adopt proactive advertising during a recession whilst others favor cutting their communication investments (see Srinivasan et al. 2005, and Deleersnyder et al. 2009). However, the majority of companies cut their advertising budget during such times (Barwise and Styler, 2002, 2003; Picard, 2001). Some authors have found a stable ratio between aggregated advertising expenditure and real GDP (see Van der Wurff and Bakker, 2008). At a more disaggregated level, magazine and newspaper advertising is more sensitive to the economy than TV, whilst radio advertising shows little sensitivity (see Deleersnyder et al., 2009). But in general, the literature does not consider structural breaks caused by new media introductions over the last century, nor the long-term equilibrium between shares of the different media (after the structural breaks have been removed). Even more importantly, we do not know the crossed elasticities between the different channels in the long-run.

Nowadays this is a relevant issue; and the most recent example is the growing trend on Internet's share which is partially replacing radio, newspapers and magazines ad expenditures. But these phenomena occurred frequently in the past, and in order to understand the impact of new media introduction we need to look back at the last century, where we can observe it through several historical landmarks.

- The first newspaper in the US appeared in Boston in 1690. Since then, newspaper growth continued unabated until the first third of the 20th century. Between 1890 and 1920, the period known as the

golden age of print media, William Randolph Hearst, Joseph Pulitzer and Lord Northcliffe built huge publishing empires. From the 1920s, radio broadcast increasingly forced newspapers to re-evaluate their business, and the same happened in the 1950s when TV broadcasting exploded onto the media scene. During the second part of the 20 century Newspaper circulation dropped, and the ad expenditure budget show this impact.

- The first radio broadcast was in 1906, but its golden age in the US spans from the early 1920s, when the first broadcast licenses were granted, until the 1950s when it was replaced by TV as the primary entertainment media. Initially, individual radio programs were sponsored by a single business, but gradually they started to sell small time allocations to multiple businesses. Commercial advertising was not generalized until the 1940s.
- The TV business started out in the 30s but actual household penetration took-off after the Second World War, evolving slowly into an advertising based business whereby Procter & Gamble, Unilever and other companies started to develop commercials for Soap Opera's. In the 1950s advertisement time was sold to multiple sponsors. From the 1960s big campaigns featured different mass media channels such as TV, radio and magazine extensive advertisement.

Marketing researchers have studied how new product/brand launches and exits in a market affect the competitive setting faced by incumbent companies. For example, Nijs et al. (2001) study the new product introductions as a way to expand permanently the category demand. Fok and Franses (2004) analyze marketing mix effectiveness of incumbents resulting from a new brand introduction. Pauwels and Srinivasan (2004) examine how store brand entry structurally changes the performance of and the interactions among all market players. Moreover, Van Heerde et al. (2004) investigate how the innovative product alters the structure of market dynamics. Allowing for multiple breaks at unknown points in time, Kornelis et al. (2008) explores to what extent competitive entry might not just be a temporal nuisance to incumbents, but could also fundamentally change the latter's performance evolution.

Historical evidence shows that introduction of new media can shake the advertisement industry. To appraise the growth prospects of advertising in the available media, we need to model the long-term equilibrium, and to estimate the substitutability and complementarity patterns. But we also need to model the structural breaks caused by media introduction over the incumbents. Did the introduction of new media (TV, Yellow Pages, cable and Internet) create a fundamental (structural) change in the advertising industry? If we remove the introductions' effect, what can we say about persistent relationships and how each media is influenced by the business cycle in the long-term? In this paper, we address these questions.

This is a challenging problem. As advertising expenditure and GDP are non stationary time series (they tend to grow steadily), we need to use specific multivariate time series models with stochastic common trends allowing structural breaks. In particular, we will model the dynamic interactions through Vector Error Correction Mechanism (VECM) model allowing multiple structural breaks due to the entry of the new media (TV, Yellow Pages, cable and Internet).

The paper is organized as follows: In the next section, we will introduce the data and the preliminary analysis on unit root and cointegration tests. In particular, we will study annual time series data ranging from 1935 to 2007 on ten different media channels: newspapers, magazines, direct mail, business papers, outdoor, radio, TV, Yellow Pages, cable and the Internet. In section 3, we will present the results of the disaggregated model in which we use aforementioned media channels and the GDP. In section 4, we will discuss the results of the aggregated model in which we will use only the total advertising spending and the GDP. Finally, we will conclude the paper with a summary of the main findings.

Data and preliminary analysis

There are several sources to compile data for US advertising expenditure. One of the oldest databases is the McCann-Erickson-Magna database. In 1935, L.D.H. Weld, Director of Research for McCann-Erickson and formerly professor of Business Administration, at Sheffield Scientific School, Yale University, published advertising data in the magazine *Printers' Ink*. Robert J. Coen joined McCann-Erickson in 1948 and two years later Weld died. Coen took up the compilation from 1950 until 2008 when he retired as vice president and forecasting director at the media agency. An early version of this work was published in the Census Bureau (1970, Part II, pages 855-7). The Television Advertising Bureau has made a recent version of Coen's data available online. This recent version covers the period from 1948 to 2007. These data were completed by Dr. Douglas A. Galbi, economist at Federal Communications Commission. He added Coen's data to the period from 1919 to 1947. He also included some categories of advertising expenditure for the period spanning from 1919 to 1934. As a result, the final version of the compiled dataset covers the yearly data from 1919 to 2007 and contains the advertising expenditure on the following media: newspapers, magazines, direct mail, business papers, billboards, out of home, Yellow Pages, radio, television, broadcast, cable, the Internet and total advertising. We have totaled the advertising expenditure on 'out of home' and 'billboards' as the former

was the antecedent of the latter, and called the new variable 'outdoor'. We have followed the same approach for 'television' and 'broadcast', and called the final variable TV. We have also obtained the real GDP variable from the U.S. Department of Commerce, Bureau of Economic Analysis for the period of 1929 and onwards in order to account for the impact of economic crisis and expansions in the advertising industry.

Finally, our dataset is comprised of the following variables: newspapers, magazines, direct mail, business papers, outdoor, radio, TV, Yellow Pages, cable, the Internet, total advertising and GDP. For analytical purposes, we have chosen the time period 1935-2007 so as to have less missing variables in the system. Figure 1 plots the series at their original levels. In general, we can observe exponential trends in the series, however, after the year 2000, TV, newspapers and radio advertising spending show a decreasing pattern. By contrast, direct mail, cable and Internet advertising spending exhibit an increasing pattern. Outdoor advertising spending shows a sharp increase in 1999 which continues in the following periods.

Insert Figure 1 about here

In order to make the series more linear, we took the natural logarithm for all variables. As can be seen from Figure 2, the entry times of the four new media (TV, Yellow Pages, cable and Internet) to the industry can be detected easily. For a given media, observations before the break point where the media takes-off are recorded as zeros. We acknowledge that the introduction times can potentially change the dynamic structure.

Insert Figure 2 about here

Visually, it seems that all the log-transformed series are integrated of order one, or $I(1)$, which means that their growth rate is stationary (stable over time). Moreover, they seem to evolve in parallel driven by common trends according to certain long-term equilibrium defined by a cointegration relationship, implying that the dynamics of this market can be represented by a Vector Error Correction Mechanism (VECM) model. These econometric concepts are standard in the Time Series literature and increasingly used in marketing (see Dekimpe et al. 1999), but for readers not familiar with these concepts we have provided some technical explanations in the Appendix. The interesting feature is that the common trend components between these series does not seem to change once the impact of a new introduction wares

off, so that structural changes seem not to have an impact on the long run equilibrium (the cointegrating vector) but just on the short term adjustments to the equilibrium after the introductions.

In this paper, we deal with two distinct time series models: (1) a disaggregated model, where we consider a time series vector for $X_t = (\ln GDP_t, \ln m_t')'$ where GDP_t denotes the gross domestic product and the column vector $\ln m_t$ means logarithm of expenditures on the different media by birth order (newspapers, magazine, direct mail, business papers, outdoor, radio, TV, Yellow Pages, cable and the Internet advertising spending) in the United States, and we allow for structural breaks associated to new media introductions, and (2) an aggregated model with structural breaks, where we study the bivariate time series for $Y_t = (\ln GDP_t, \ln TA_t)'$ where TA_t denotes total advertising expenditure, and we include also the media introductions structural breaks. Before delving into the analysis of each model, we will first test formally if the time series process is $I(1)$, and then we will check if the vector time series are cointegrated.

Unit root tests

As we have mentioned before, graphical inspection of Figure 2 suggests that the series are integrated of order one. Inspection of the Auto Correlation Function (ACF) plots for the original and the differentiated series suggests that the series are $I(1)$. We have also run several formal tests, such as the Augmented Dickey Fuller (ADF) unit root tests (see Banerjee et al., 1993). This preliminary analysis suggests that X_t is an $I(1)$ process.

We have also performed the ADF tests and take into account that unit root tests for the new media (TV, Yellow Pages, cable and Internet) can be dramatically affected since structural breaks occur in the series (see Perron, 1989). In the ADF tests, we have adopted two options: (i) only stochastic trend in the series, (ii) both deterministic trend and stochastic trend in the series. For both the aggregated and the disaggregated model, we have found that the latter option is more appropriate since the coefficient of the deterministic trend is significant for most of the considered series. Table 1 summarizes the ADF unit root test results. For all variables, we fail to reject the null hypothesis of the ADF test that the series contains a unit root. Thus, the ADF unit root tests support our preliminary findings based on correlogram analysis.

Insert Table 1 about here

Cointegration

In this section, we will carry out an exploratory analysis for the cointegration of the considered variables. Cointegrating tests can also be affected dramatically by the presence of structural breaks (see, Johansen, 2000). More specifically, to determine the rank of the cointegrating matrix β , we have adopted the following sequential hypothesis testing. By using STATA-10 and OX version 3.4 (see Doornik, 2001), first, we tested the null hypothesis that there is no cointegration against the alternative hypothesis that there is at least one cointegrating vector.

Table 2 displays the cointegration test results. In the disaggregated model, first we rejected the null hypothesis that there is no cointegration since trace statistic (263.473) is greater than its critical value (233.130). Next, we test the null hypothesis that there is one cointegrating vector. We have not rejected the null hypothesis as the trace statistic (186.592) is smaller than its critical value (192.890). Therefore, the conclusion for the disaggregated model is that there is one cointegrating vector. We have followed the same approach for the aggregated model. We the null hypothesis that there is no cointegration was rejected, but we have not rejected the null hypothesis that there is one cointegrating vector because the trace statistic (2.993) is less than its critical value (3.760). Thus, there is one cointegrating vector in the aggregated model as well.

Insert Table 2 about here

Then, we estimated the vector error correction models accounting for the potential effect of structural breaks. More specifically,

- The disaggregated model studies the long run relationship between the GDP and the advertising spending on ten different media: newspapers, magazines, direct mail, business papers, outdoor, radio, TV, Yellow Pages, cable and the Internet
- The aggregated model provides a synthetic picture of the industry. It studies the dynamic pro-cyclicality or counter-cyclicality of the total advertising expenditure and the GDP, both in logarithm.

Disaggregated model with structural breaks: Main Results

Notice that TV and Yellow Pages were introduced to the industry in 1949 and 1980 while cable and the Internet in 1990 and 1997, respectively. As different media channels entered the market at different points in time, we should consider structural breaks for the whole system, whenever a new media starts to be exploited by the advertising industry. As discussed earlier, persistence and cointegration tests can be dramatically affected by the presence of structural breaks. Structural breaks typically have little effect on the size of the usual cointegration tests, but they affect the power of the tests. There is a significant literature focusing on cointegration under known or unknown structural breaks. Maximum likelihood procedures, as the Johansen (1991, 1994) test, have greater power than the Dickey-Fuller based cointegration tests. The Johansen test requires modeling the break, but this is less restrictive in our context, where the break time is observed. Next, we will follow the Johansen (1991, 1994) framework to estimate the impact of new media introductions on advertising dynamics, see the Appendix for a short introduction.

Let us assume that there are structural changes associated with the introduction of new media (TV, Yellow Pages, cable and Internet). Let $T = (T_1, \dots, T_k)'$ be the introduction times of the k different media. We consider that the introduction times are deterministic (exogenous variables and we condition the process upon their value). The introduction of a new media may cause a permanent structural change in the growth rates of incumbent media (intervention analysis). Therefore, if the system grows at an autonomous vector rate γ until the structural breaks occur, and at a different rate after the launch of a new media, then we can consider a deterministic component $\mu_t = E[X_t]$ given by

$$\mu_t = \mu_0 + \gamma t + \Phi F_t,$$

where F_t is a deterministic vector with j -th coordinate $\max\{t - T_j, 0\}$ equal to zero for $t < T_j$ and to $t - T_j$ for $t \geq T_j$, so that F_t is formed by as permanent shifts starting at new media introductions.

The matrix Φ contains the crossed effects of all new media launching on the deterministic component of other media. Then, for $t \geq 1$,

$$\Delta\mu_t = E[\Delta X_t] = \gamma + \Phi D_t,$$

where D_t is a deterministic vector of step functions, such that the j -th coordinate is defined as

$D_{jt} = I(t \geq T_j)$ where $I(t \geq T_j)$ is the indicator function taking the value one if $t \geq T_j$ and zero

otherwise. We impose some restrictions on the coefficient matrix Φ . It must have a triangular media-structure, as we impose the restrictions that new media introductions in the advertising market do not affect investments on media launched on the distant future. Therefore, (i) TV introduction cannot cause any structural change in Yellow Pages since TV enters the market before Yellow Pages, (ii) TV and Yellow Pages cannot cause any structural change in cable series because TV and Yellow Pages enter the market before cable, (iii) TV, Yellow Pages and cable cannot cause any structural change in the Internet as it was launched after all of these channels.

The VECM representation indicates that the current increment in X_t depends on previous deviations from the long-run equilibrium, the effect of deterministic components D_t , and previous corrections ΔX_{t-j}

$$\Delta X_t = \alpha(\beta'X_{t-1}) + \sum_{j=1}^p \Gamma_j \Delta X_{t-j} + (\gamma + \Phi D_t) + \varepsilon_t.$$

We have included the deterministic trend in the VECM model as $E[\Delta X_t] = \gamma$, based on our preliminary finding from the ADF unit root tests. Now β is the cointegration vector, and $\beta'(X_t - E[X_t]) = 0$ is a long-term equilibrium relation between the coordinates in the vector X_t . The VECM models indicates that the change ΔX_t evolves driven by its lags $\{\Delta X_{t-j}\}$ with diminishing weights Γ_j , but it is also affected by previous deviation from the equilibrium relationship, $\beta'X_{t-1}$, with corrections controlled by the parameters in α .

The parameters $(\alpha, \beta, \Gamma_1, \dots, \Gamma_p, c, \Phi, \Omega)$ are freely varying, but we have normalized β to estimate the individual coefficients. The cointegrating rank of the last system is usually determined using Johansen's (1988, 1991, 1995) maximum eigenvalue and trace tests. Johansen also considered the Maximum Likelihood estimators of the full model, and the asymptotic distribution. For details see Johansen et al. (2000) and Hungnes (2010). Pesaran et al. (2000) extend these ideas about deterministic components μ_t to models with exogenous process. The model is estimated by maximum likelihood method using OX version 3.4 and GRaM (see Hungnes, 2005). We run the models up to four lags and compute the AIC and SIC criteria. Both information criteria suggest using one lag in the final analysis. Hence, to capture the

short-term dynamics towards the identified long-term equilibrium, we have estimated the VECM model with $r = 1$ (one cointegrating vector) and $p = 1$.

From the estimation output, parameters α are deemed as short-term error-adjustment parameters whereas parameters β are regarded as long-term equilibrium relationship parameters. Table 3 shows the estimated cointegration vector (β), and the estimated (α) measuring the response of each variable to deviations from each cointegration equilibrium relationship. Estimated α coefficients reveal that newspaper, direct mail and TV respond to the disequilibrium in the system as they are significant at 5% level. Moreover, the estimated α for TV is higher implying that the advertising investment in this new media is more sensitive to deviations from the long-term equilibrium than those in the other media.

Insert Table 3 about here

Based on the estimated β vector in Table 3, we can also compute the long-term elasticities (Table 4). Notice that the series in the vector X_t are all in logarithms. Let us denote by Z_t the original series, and $X_t = \ln Z_t$. If we differentiate the equilibrium $\beta' \ln Z = 0$, and we denote by k the number of variables we obtain that:

$$\beta_1 \frac{d \ln Z_1}{dZ_1} + \dots + \beta_k \frac{d \ln Z_k}{dZ_k} = 0$$

If we vary two components i, j and set all the other variations to zero, then the cross elasticity between the advertising invested in two media becomes

$$\eta_{ij} = \frac{d \ln Z_i / dZ_i}{d \ln Z_j / dZ_j} = - \frac{\beta_i}{\beta_j}$$

where η_{ij} refers to the elasticity of media i expenditure with respect to that of media j . It is interpreted in the sense that a lasting 1% increase of expending in media i results in η_{ij} % increase in media j in the long run equilibria. The reverse elasticity is $\eta_{ji} = 1/\eta_{ij}$. This is a measure of how one media substitutes another in the long run equilibrium. If $\eta_{ij} > 0$ both media are complementary in the long run, if $\eta_{ij} < 0$ then i and j are substitutive media. Silk et al (2001) consider that a pair of media are more likely to be treated as substitutes rather than complements if they offer advertisers (1) similar levels of

audience target addressability, (2) different levels of audience power to control their exposition to advertisement, and (3) different levels of flexibility in contractual requirements (e.g., regarding lead-time, duration, and cancellation).

Table 4 reports the long run cross-elasticities η_{ij} between the different channels at equilibrium (i are rows and j columns), and also with respect to GDP. Notice that, as the coefficient β associated to the logarithm of the GDP is normalized to one, the elasticity of any media with respect to the GDP is simply the respective coefficient in Table 3 with a sign change. It is positive for newspapers, magazines, outdoors, and cable, but negative for direct mail, business papers, radio, TV, Yellow Pages and the Internet, so that lasting changes in GDP tend to reshape the long run distribution of advertising expenditure across media. We can now examine the long run impact of the Internet over advertising on different media. The cross-elasticity of newspapers with respect to the Internet is 2.169 , and similarly that of magazines (2.401), outdoor (1.234) and cable (0.606) are positive. However, for direct mail it is negative (-2.618) which suggests that mailing is increasingly channeled via Internet, it is also negative for business papers (-1.186) probably because consumers look for economic information on the Internet, it is also negative for classical mass media such as radio (-1.005) and TV (-1.409), which could evidence that the audience increasingly consumes free entertainment on the Internet. Notice also that in the long-term radio and TV are substitutes (-2.454), but TV and cable are complementary, attracting advertising expenditure (0.675).

Insert Table 4 about here

The cross-elasticities show the long-term impact of changes in one media advertising expenditure on another, after discounting the impact of new media introductions. But the introductions have a direct impact on the expected growth rates of the incumbents via the expression $E[\Delta X_t] = \gamma + \Phi D_t$. Table 5 shows the estimation of Φ the matrix of structural change effects. In particular, the introduction of TV, Yellow Pages and the Internet has had a negative impact on most incumbents but not all, and in some cases the effect was insignificant. Cable, on the contrary, has had a positive impact on most incumbents. If we examine Internet more carefully, its introduction has had a negative impact on magazines, business

papers, outdoors, radio and TV, a positive impact on direct mail, and insignificant on Yellow Pages and newspapers.

Insert Table 5 about here

We have also checked actual versus predicted series pertaining to the disaggregated model. As can be seen from Figure 3, our model predicts the system dynamics relatively well.

Insert Figure 3 about here

Aggregated model with structural breaks: Main Results

The aggregated model provides a general picture of the advertising industry. In the model, we have used total advertising expenditure and GDP (both in logarithm). We also include the structural break dummies to see whether or not the new media affected the structure of the overall budget. Our results show that none of the structural dummies was significant. In addition, the estimated α coefficients indicate that both variables respond to the disequilibrium in the system as they are significant at 1% level, but total advertising is faster than GDP. In the aggregated model, we focus on the estimated cointegrating vector β to examine whether the total advertising spending and GDP moves in the same direction in the long run, where the coefficient of $LnGDP$ is normalized to one. The estimated β in Table 6 shows us the long-term elasticity since both variables are expressed in logarithm. As with the disaggregated model, we normalized GDP in the cointegrating vector. Thus, the long run elasticity between of total advertising spending with respect to GDP is 1.529, implying that a 1% increase in GDP will result in a 1.52% growth in total advertising spending.

Insert Table 6 about here

Figure 4 shows actual versus predicted series of the aggregated model. The plots demonstrate that our model captures the system dynamics well.

Insert Figure 4 about here

Conclusions

In this paper, we have studied empirically whether the entries of new advertising media affected the growth rates of incumbents' expenditures in the form of creating fundamental change. We have used the annual time series data on ten different advertising media channels in the U.S. at the aggregate level and build a VECM model allowing for structural changes. Our proposed methodology allows for modeling both short- and long-term dynamics among the variables and takes into account multiple structural breaks that occur at the entry times of TV, Yellow Pages, cable and Internet advertising media. We apply our dataset to two distinct models: disaggregated and aggregated.

Based on the aggregated model, we have found that total advertising spending is pro-cyclical, i.e., it moves in the same direction as GDP in the long run. This result is in line with the findings in the related literature: Jones (1985), Callahan (1986), and Deleersnyder et al. (2009). Based on the disaggregated model, we find that new media caused substantive shift in the growth rates of almost all incumbents. TV, Yellow Pages and the Internet introduction harmed most established media, whereas cable generally has had a positive impact. Regardless of the introduction impact, the cointegration vector provides perspective of how cross-elasticities work in the long run equilibrium, in particular the cross-elasticities show that Internet is complementary for several media such as Newspapers, Magazines, cable, and Outdoor, and substitutive for direct mail, business papers, radio and TV. As expected, radio and TV are substitutes, but TV and cable are complementary in the long run. The study suggests that there are two types of effects, the structural break caused by the mean shift and the long run equilibrium relationships showing the substitutive/complementary patterns between the different media. Clearly, the Internet is going to have a long-term impact on incumbent media, but not always negative. In particular, the long run cross-elasticity is positive for newspapers, magazines, outdoor and cable. But it is negative for radio and TV. Radio and TV are mutually substitutive, but both are complementary with respect to cable.

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Tables

Table 1. ADF unit root tests

Variables	ADF test result (<i>p</i> -value)		Conclusion
	Intercept	Intercept and Trend	
LnNewspapers	0.701	0.958	I(1)
LnMagazines	0.716	0.589	I(1)
LnDirect Mail	0.947	0.182	I(1)
LnBusiness Papers	0.099	0.853	I(1)
LnOutdoor	0.978	0.735	I(1)
LnRadio	0.518	0.762	I(1)
LnTV	0.382	0.854	I(1)
LnYellow Pages	0.884	0.609	I(1)
LnCable	0.953	0.834	I(1)
LnInternet	0.973	0.958	I(1)
LnGDP	0.701	0.515	I(1)
LnTotal Ads	0.793	0.883	I(1)

Table 2. Johansen's cointegration test

Maximum Rank	Log Likelihood	Eigenvalue	Trace Statistic	5% Critical Value
<i>Disaggregated Model</i>				
0	349.981	.	263.473	233.130
1	388.421	0.656	186.592*	192.890
2	412.322	0.485	138.790	156.000
<i>Aggregated Model</i>				
0	234.359	.	18.272	15.410
1	241.999	0.191	2.993*	3.760
2	243.495	0.041		

Table 3. Estimated adjustment coefficients α and cointegration parameters β
(Disaggregated Model)

<i>Estimated α coefficients</i>		<i>Estimated β parameters</i>	
LnGDP	0.018	LnGDP	1.000
LnNewspapers	-0.152**	LnNewspapers	-3.677
LnMagazines	-0.044	LnMagazines	-4.070
LnDirect Mail	-0.204**	LnDirect Mail	4.437
LnBusiness Papers	0.023	LnBusiness Papers	2.011
LnOutdoor	-0.165	LnOutdoor	-2.091
LnRadio	-0.055	LnRadio	1.703
LnTV	-0.212**	LnTV	0.694
LnYellow Pages	-0.278	LnYellow Pages	0.341
LnCable	0.043	LnCable	-1.028
LnInternet	-0.090	LnInternet	1.695

Note: ** sign implies that the associated α coefficient is significant at 5% level.

Table 4. Cross-elasticities & Elasticities of all media with respect to GDP

Table 4. Cross-elasticities & Elasticities of all media with respect to GDP											
	GDP	News.	Magaz.	D. Mail	Bus. Pap.	Outdoor	Radio	TV	Y. Pages	Cable	Internet
Newsp.	3.677	1	-0.903	0.829	1.828	-1.758	2.159	5.298	10.783	-3.577	2.169
Magazines	4.070	-1.107	1	0.917	2.024	-1.946	2.390	5.865	11.935	-3.959	2.401
D. Mail	-4.437	1.207	1.090	1	-2.206	2.122	-2.605	-6.393	-13.012	4.316	-2.618
Bus. Pap.	-2.011	0.547	0.494	-0.453	1	0.962	-1.181	-2.898	-5.897	1.956	-1.186
Outdoor	2.091	-0.569	-0.514	0.471	1.040	1	1.228	3.013	6.132	-2.034	1.234
Radio	-1.703	0.463	0.418	-0.384	-0.847	0.814	1	-2.454	-4.994	1.657	-1.005
TV	-0.694	0.189	0.171	-0.156	-0.345	0.332	-0.408	1	-2.035	0.675	-0.409
Y. Pages	-0.341	0.093	0.084	-0.077	-0.170	0.163	-0.200	-0.491	1	0.332	-0.201
Cable	1.028	-0.280	-0.253	0.232	0.511	-0.492	0.604	1.481	3.015	1	0.606
Internet	-1.695	0.461	0.416	-0.382	-0.843	0.811	-0.995	-2.442	1.649	1.649	1

Table 5. Estimated dummy coefficients (Disaggregated Model)

	LnNewspapers	LnMagazines	LnDirect Mail	LnBusiness Paper	LnOutdoor	LnRadio	LnTV	LnYellow Pages	LnCable	LnInternet	LnGDP
D _{TV}	-0.104**	-0.570***	0.461***	-0.433***	-0.032	-0.008	0.000	0.000	0.000	0.000	-0.341***
D _{Yellow Pages}	-2.594***	-0.522***	-4.138***	1.403***	-2.883***	-1.518***	2.697***	0.000	0.000	0.000	0.790***
D _{Cable}	2.387***	2.105***	1.752***	1.888***	4.141***	2.539***	0.340	2.847***	0.000	0.000	1.244***
D _{Internet}	0.312	-0.532*	1.039**	-0.710**	-2.796***	-0.217	-0.750	1.678	-0.923	0.000	-0.216

Notes: ***, **, * signs imply that the associated coefficient is significant at 1%, 5% and 10% level, respectively.

Table 6. Estimated adjustment coefficients α and cointegration parameters β (Aggregated Model)

<i>Estimated α coefficients</i>		<i>Estimated β parameters</i>	
LnGDP	-0.072***	LnGDP	1.000
LnTotal Ads	-0.090***	LnTotal Ads	-1.529

Note: *** sign implies that the associated α coefficient is significant at 1% level.

Figures

Figure 1. USA advertising expenditures (in million \$) over time

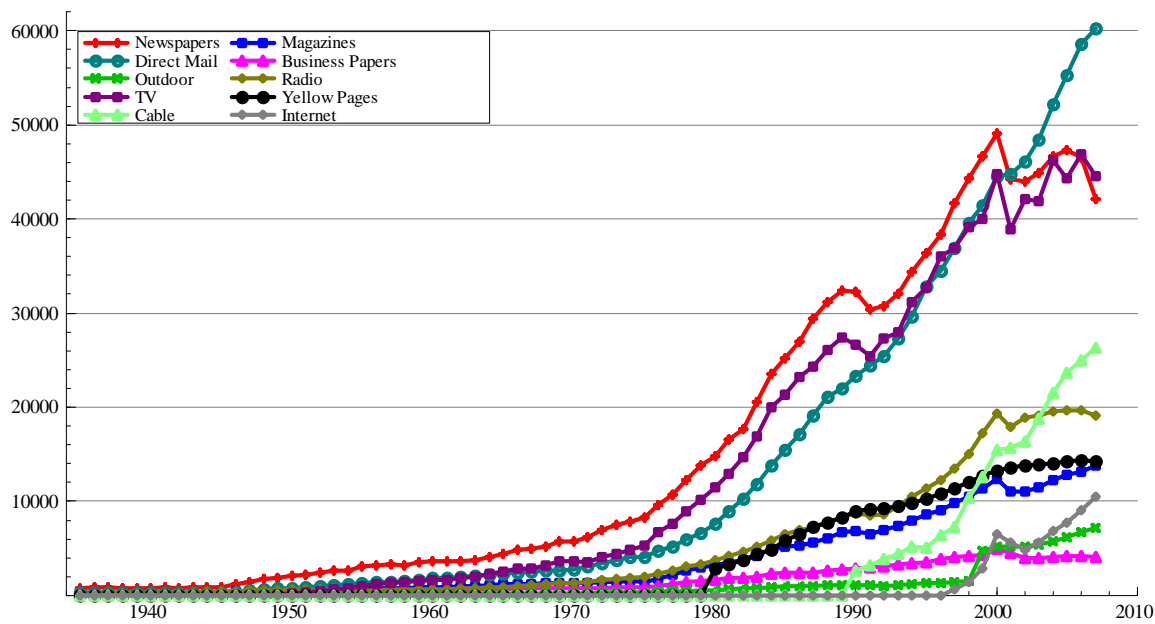


Figure 2. Log. of USA Advertising and GDP (million \$)

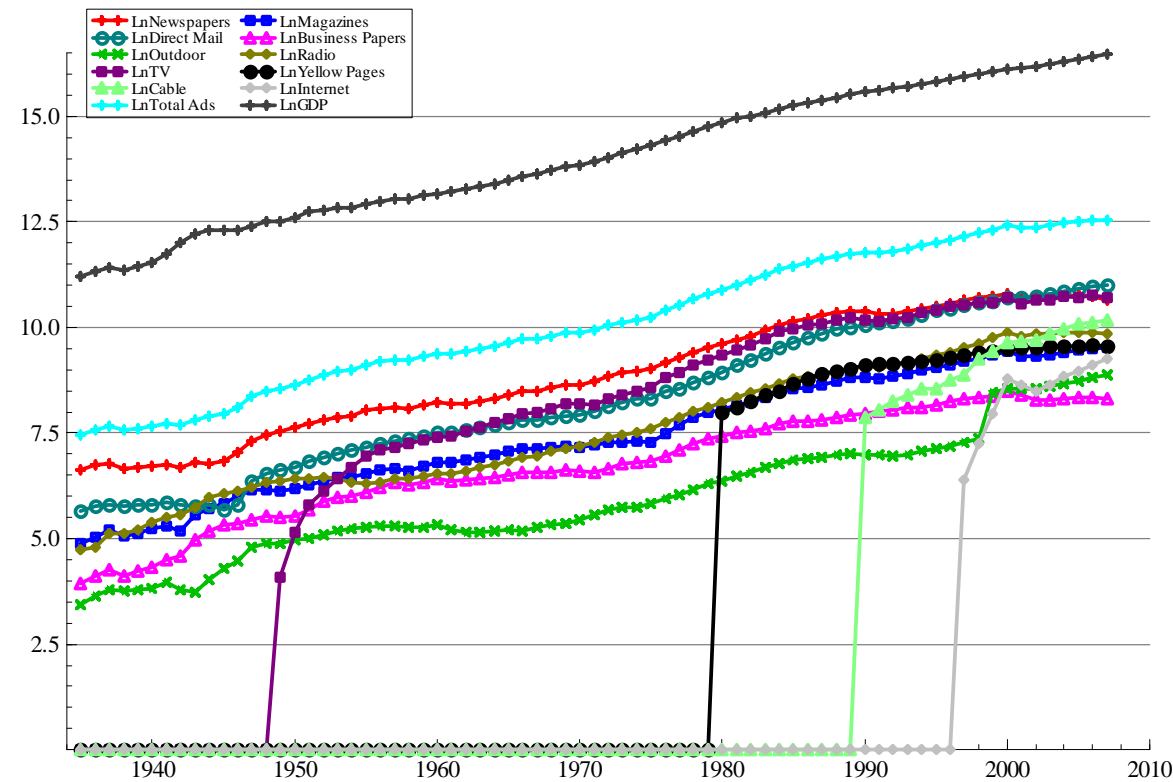


Figure 3. Actual versus predicted series (Disaggregated Model)

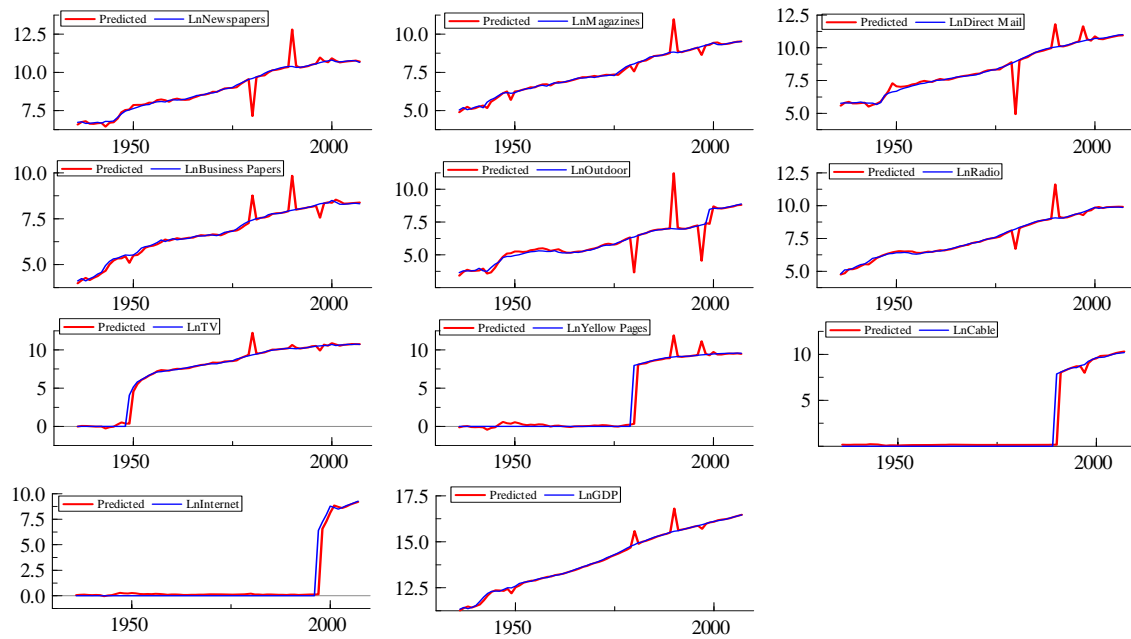
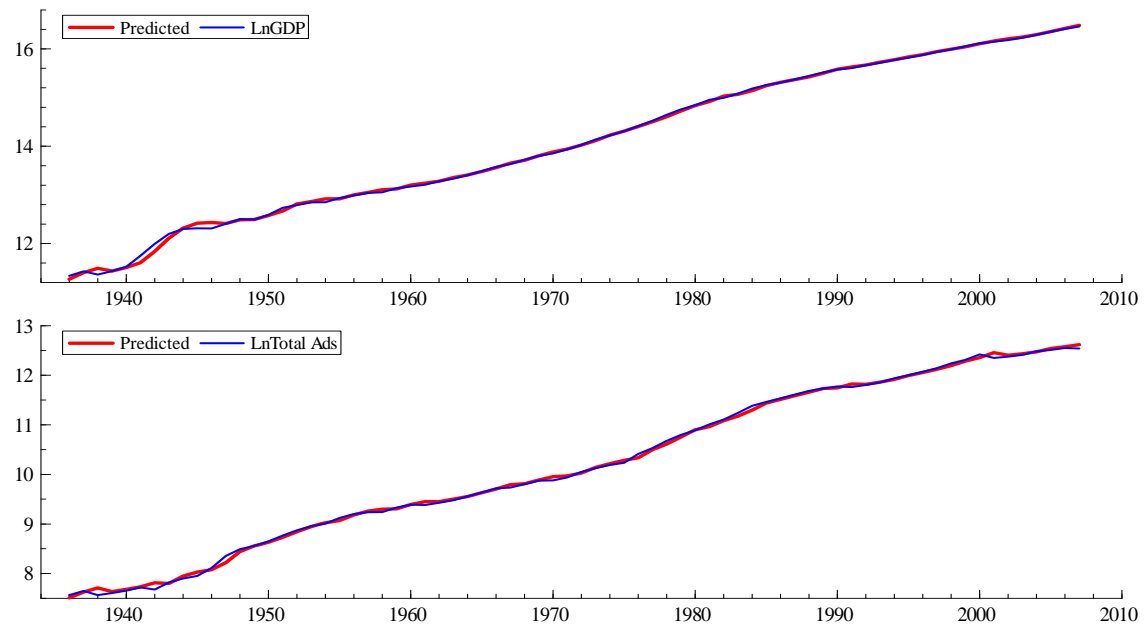


Figure 4. Actual versus predicted series (Aggregated Model)



Appendix

Let us denote by X_t a \mathbb{R}^k -valued stochastic time series process with unconditional mean $\mu_t = E[X_t]$, where $X_t = 0$ with probability one for $t \leq 0$ (with finite autoregressive models sometimes other specific initial values are considered). The mean $\mu_t \in \mathbb{R}^k$ contains deterministic components (trends, intervention analysis components, etc.). Typically, but not always, the deterministic components are subtracted (if that is the case, then $\mu_t = 0$ for all t). Then, we say that $\{X_t\}$ is **integrated** of order $d \in \{0, 1, 2, \dots\}$, also denoted as $I(d)$, if **each coordinate** in $\Delta^d X_t$ follows an invertible stationary linear model, where $\Delta^d = (1 - L)^d$ and L is the lag operator ($L^j X_t = X_{t-j}$). One of the most common cases in practice, is to find processes X_t integrated of order one (in this case the components of the process tend to grow linearly as in the case of Figure 2). In particular, if X_t is $I(1)$, then $\Delta X_t = (X_t - X_{t-1})$ is stationary, and there are two possibilities (1) that $E[\Delta X_t] = 0$ which means that X_t evolves driven by a stochastic trend, or that $E[\Delta X_t] = \gamma$ which means that ΔX_t has a deterministic and/or a stochastic trend.

Example A basic example of a determinist trend is the univariate process

$$X_t = c + \gamma t + \varepsilon_t, \quad t = 0, 1, 2, \dots$$

where ε_t are i.i.d. random variables with zero mean and variance σ_ε^2 , where clearly ΔX_t is stationary and $E[\Delta X_t] = \gamma$. A basic example of stochastic trend is the univariate process

$$X_t = X_{t-1} + \varepsilon_t, \quad t = 0, 1, 2, \dots$$

with $X_0 = 0$, with $E[\Delta X_t] = 0$. Substituting recursively we obtain $X_t = \sum_{s=1}^t \varepsilon_s$, so that $E[X_t] = 0$ but $\text{Var}[X_t] = t\sigma_\varepsilon^2$ exploding as $t \rightarrow \infty$. The shocks ε_s have a permanent effect in the future, this is why these processes are described as persistence. The name unit root is also used for these models (because they can be expressed as $(1 - L) X_t = \varepsilon_t$, and $L = 1$ is a root of the polynomial $(1 - L) = 0$). We can have a combination of deterministic and stochastic trends, such as $X_t = c + \gamma t + X_{t-1} + \varepsilon_t$, where $E[\Delta X_t] = \gamma$, and the series in

levels satisfies $E[X_t] = c + \gamma t$, and $Var[X_t] = t\sigma_\varepsilon^2$. In all these examples $\{\varepsilon_t\}$ could follow a stationary linear process.

Since the presence of linear trends (stochastic or deterministic) is important to understand the long-term dynamics of the process, there are many tests for $I(1)$, for an overview of unit root literature see Banerjee et al. (1993), and for a review of marketing applications see Dekimpe et al. (1999).

But we are interested in multivariate processes, and this introduces additional issues. When a multivariate process $\{X_t\}$ is $I(1)$, two possibilities emerge when we look at the whole system:

- 1) $\{X_t\}$ is **jointly integrated** of order d , that is, it is integrated of order d and $(1-L)^d X_t$ follows

an invertible vector Wold process $\Delta^d X_t = B(L)\varepsilon_t$ with ε_t white noise (actually ε_t is zero for $t \leq 0$), $B(L) = \sum_{j=0}^{\infty} B_j L^j$ is a matrix-coefficient polynomial with $B_0 = I$ (where invertibility means that the roots of $|B(L)|$ are outside the unit circle, and the process admits a convergent autoregressive representation), or

- 2) $\{X_t\}$ is **cointegrated** of order d, b with $b \leq d$, and denote it by $C(d, b)$, that is the process is

$I(d)$ and there are $r \leq k$ linear combinations defined by the $k \times r$ matrix β such that $\beta'X_t$ is jointly $I(d-b)$. The most important case is $d = b = 1$. The idea goes back to Box and Tiao (1977), but it was popularized by Granger (1981). Cointegrated $C(1, 1)$ variables can be expressed with Granger's representation Vector Error Correction Mechanism or VECM,

$$\Delta X_t = \alpha(\beta'X_{t-1}) + \sum_{j=1}^{\infty} \Gamma_j \Delta X_{t-j} + \gamma + \varepsilon_t, \text{ where } \alpha \text{ is the } k \times r \text{ matrix of adjustment}$$

coefficients. The matrix of cointegrating vectors β can be normalized as $\beta = \begin{pmatrix} I_r \\ \beta_2 \end{pmatrix}$ where I_r is

an identity matrix, and β_2 is a $(k-r) \times r$ matrix of free parameters. For details see the path-

breaking article by Engle and Granger (1987). For a detailed introduction see Banerjee et al. (1993).

There are several methodologies to work with VECM models. Probably the most widespread approach is the Johansen (1991, 1994, 1995) framework which we will follow. In this context, we can introduce deterministic components D_t to handle structural breaks. Instead of subtracting the deterministic

components from X_t , Johansen (1995) directly assumes that X_t follows an integrated $VAR(p)$ vector autoregression

$$\Delta X_t = \Pi X_{t-1} + \sum_{j=1}^p \Gamma_j \Delta X_{t-j} + (\gamma + \Phi D_t) + \varepsilon_t,$$

The error vectors $\{\varepsilon_t\}$ are assumed to be Gaussian white noise $N(0, \Omega)$. Johansen considers the characteristic lags matrix polynomial

$$A(L) = (1 - L)I_k - \Pi L - \sum_{j=1}^p \Gamma_j (1 - L)L^j.$$

In this context, if all the roots of the polynomial $|A(L)|$ are outside the unit circle (so that $A(1) = -\Pi$ has full rank), then the process is jointly integrated. However, if there are $(k - r)$ roots equal to 1 and the remaining roots are outside the complex unit circle, then $A(1) = -\Pi$ has rank r , and we can express $\Pi = \alpha\beta'$, where α, β are $k \times r$ matrix of rank $r < k$, rendering the VECM representation (main). Note that the model (AR) can be also written in differences as

$$(\Delta X_t - E[\Delta X_t]) = \alpha(\beta' X_{t-1} - E[\beta' X_{t-1}]) + \sum_{j=1}^p \Gamma_j (\Delta X_{t-j} - E[\Delta X_{t-j}]) + \varepsilon_t,$$

and the equation $\beta'(X_t - E[X_t]) = 0$ defines the long-run relations between the variables.

The VECM model can be estimated by Pseudo Maximum Likelihood

$$L_T(\theta) = -\frac{Tk}{2} \log(2\pi) - \frac{T}{2} \log |\Omega(\theta)| - \frac{1}{2} tr \{ \mathbb{E}(\theta)' \mathbb{E}(\theta) \Omega(\theta)^{-1} \}$$

where θ are the parameters of the model, $\mathbb{E}(\theta)$ is the matrix of VECM residuals, Ω the covariance matrix of the innovations, tr is the trace, and T the sample size. Substituting the optimal Ω , and removing constants the concentrated likelihood can be expressed as

$$L_T(\theta) = -\frac{T}{2} \log |\mathbb{E}(\theta)' \mathbb{E}(\theta)|.$$

Johansen proposed a reduced rank procedure to compute these estimators, and a sequence of maximum likelihood tests to determine empirically the cointegration rank r .